

# Analysis and End of Covid-19 in India

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## Abstract

We have collected data on Covid-19 from Arogya Set and [www.kaggle.com](http://www.kaggle.com) for India. In this case we have analysed the data on covid-19 by using regression and time series. Using these techniques, we have predicted the total positive cases, cumulative positive cases of covid-19 up to 25<sup>th</sup> July and also predicted the date when the covid-19 pandemic ends.

**Key words and phrases:** Covid-19, regression, time series, end of pandemic, India.

## 1. Introduction

COVID-19 pandemic in India is part of the worldwide pandemic of coronavirus disease 2019 (COVID-19) caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The first case of COVID-19 in India, which originated from China, was reported on 30 January 2020

On 22 March, India observed a 14-hour voluntary public curfew at the instance of the prime minister Narendra Modi. It was followed by mandatory lockdowns in COVID-19 hotspots and all major cities. Further, on 24 March, the Prime Minister ordered a nationwide lockdown for 21 days, affecting the entire 1.3 billion population of India. On 14 April, the PM extended the nationwide lockdown till 3 May which was followed by two-week extensions starting 3<sup>rd</sup> and 17<sup>th</sup> May with substantial relaxations. On 1<sup>st</sup> June the Government started unlocking the country (barring containment zones) in three steps.

As of 19 June 2020, the Ministry of Health and Family Welfare (MoHFW) has confirmed a total of 380,532 cases, 204,711 recoveries (including 1 migration) and 12,573 deaths in the country.

The prevention of spread of covid-19 has proven to be a big challenge. Moreover, the testing of suspects and treatment of infected has been another big challenge. The government/administration must be prepared with the resources required for the testing and the treatment and if they go scarce it might prove to be very troublesome in the light of surge of virus in the near future. This strenuous task can be diluted and dealt easily if the number of positive cases and can be anticipated in advance so that we are well prepared to confront this pandemic.

## About the Data

We have received the data from Aarogya-Setu and [www.kaggle.com](http://www.kaggle.com). The data available is

**Cumulative Positive:** cumulative number of positive cases

**Daily Positive:** number of positive cases found daily

**Active Cases:** the number of covid-19 active cases.

**Recovered Cases:** total number of recovered cases until a given day

For Cumulative and Daily Positive Cases, the data is considered from 2<sup>nd</sup> March 2020 to 24<sup>th</sup> June 2020 and for active and recovered cases the data is available from 4<sup>th</sup> April 2020 to 16<sup>th</sup> July 2020.

## 2. Graphical Presentation

We start with first visualizing the data through graph. The Daily +ve cases are plotted against the date in the Figure 1.

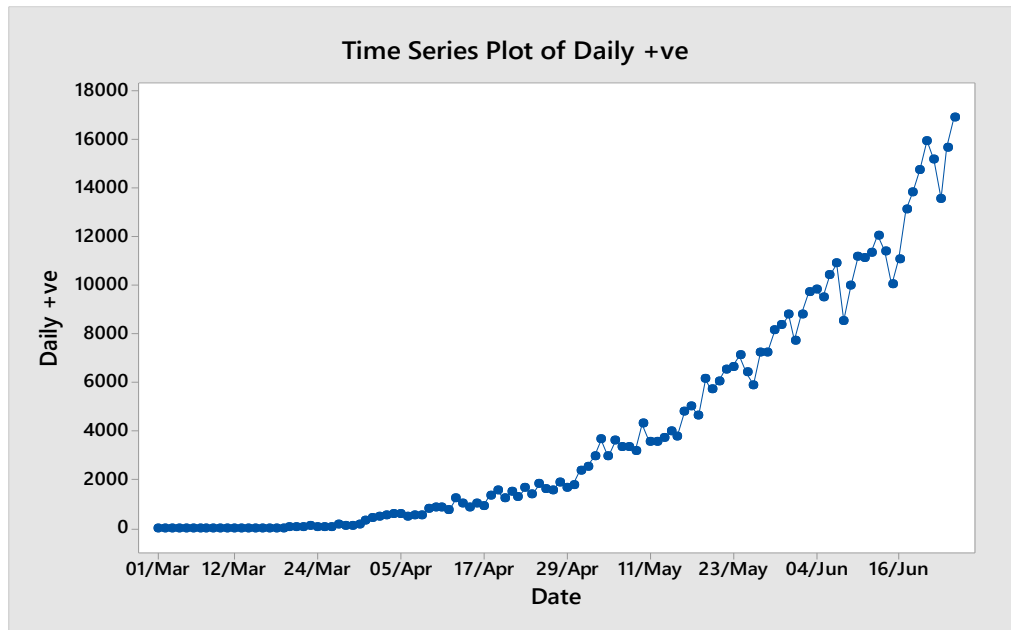


Figure 1: India

It is natural to think to model the data using regression analysis, where Daily +ve or Cumulative +ve can be taken as the response and the variable Day as the predictor if the purpose is the long-term prediction. However, the problem is, the predictor in the regression analysis is a controllable variable but there are other factors such as lockdown, invention of the drug/vaccine etc. However, despite these uncontrollable factors playing role if one can model the relationship between Cumulative or Daily +ve and Day and if it satisfies the theoretical assumptions and parameters satisfy our requirements then these models can be used for predicting the response for long term.

The prediction will be valid only if the uncontrollable factors, which determine the rate of change in the response over the time, remain roughly the same. For instance, if the government takes some drastic measures to control the spread of the virus or the vaccine of the disease is invented or for any reason in the near future then these incidents are very likely to affect the number of positive cases detected daily.

We fit the regression model for Daily +ve against Day for India.

### 3. Regression Analysis: Daily +ve versus Day

We used Minitab to assist our statistical analysis. We start with fitting the regression model for India with Daily +ve as response variable and Day as predictor. We have already seen that the relation between Daily +ve and Day is not linear but exponential. Therefore, we use Box-Cox transformation to transform the response variable. Hence, the model we fit is

$$(\text{Daily+ve})^\lambda = a + b \text{ Day}$$

Where  $\lambda$  is the parameter of the Box-Cox transformation which is to be determined. The output produced by Minitab showed that the intercept 'a' was insignificant. Therefore, we fit a model without intercept. The optimum value of  $\lambda$  produced by Minitab was 0.289171 which is very close to 0.3. The 95% confidence interval for  $\lambda$  was (0.27667, 0.30167) which contains 0.3. Therefore, we decided to

transform the response with  $\lambda = 0.3 = 3/10$  for the sake of simplicity of the model. The regression model fit is

$$(\text{Daily +ve})^{0.3} = (0.162337 \text{ Day}) \quad (1)$$

Or

$$\text{Daily +ve} = (0.162337 \text{ Day})^{10/3}$$

The ANOVA table of the model is produced in the Table 1. The p-value for regression model is too small, indicating that the model fit is overall significant.

*Table 1: Analysis of Variance for Transformed Response*

Source	DF	Adj SS	Adj MS	F-Value	P-Value
<b>Regression</b>	1	13889.4	13889.4	43628.38	0.000
<b>Day</b>	1	13889.4	13889.4	43628.38	0.000
<b>Error</b>	114	36.3	0.3		
<b>Total</b>	115	13925.7			

The Table 2 produces  $R^2$  and  $R^2$ -predicted which are 99.74% and 99.73% respectively indicating that the model is very well fit. Technically one can say that about 99.74% of the variations in Daily +ve is explained by the Day.

*Table 2: Model Summary for Transformed Response*

R-sq	R-sq(pred)
99.74%	99.73%

As the model is fit without intercept and in ANOVA we have already seen that the model is significant, there is no meaning of testing the regression coefficient again.

To assess the **validity of the assumptions** of regression model the residual plot is produced in the Figure 2.

- The residuals are satisfactorily normal and it can be seen in the NPP at the top-left corner and histogram at the bottom-left corner of the Figure 2.
- The variance of the residual is almost constant as shown by the graph of residual vs fits in the top-right corner of the residual plot.
- The Durbin-Watson Statistic for Transformed Response is 0.7321 which indicates there is positive autocorrelation among the residuals which can be observed even in the graph in the bottom-right corner of the residual plot produced in Figure 2.

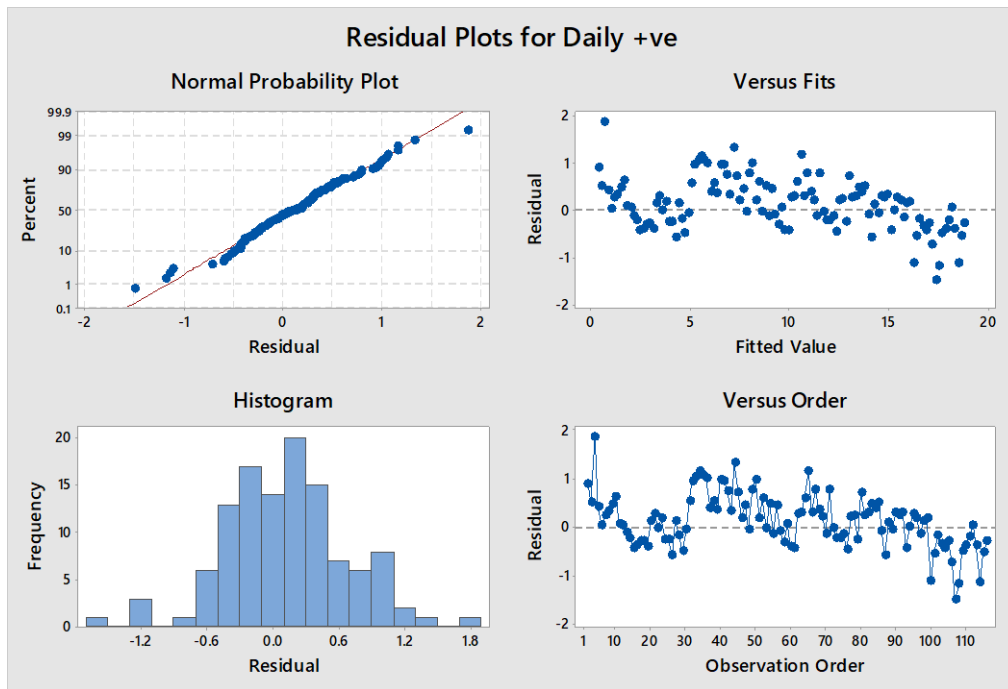


Figure 2: Residual plot

In such situation one can model the residuals using time series modelling to assist in predictions for short term but our purpose is long term prediction. Besides, the  $R^2$  is 99.67% which almost 100%. Therefore, we believe that the contribution made by the modelled errors in prediction will be negligible. Therefore, we do not go for time series modelling of the residuals.

Further, we produce the graph of the observed and fitted Daily +ve in the Figure 3 and a table of next 30 days prediction of Daily +ve and hence Cumulative +ve with 95% prediction interval in Table 3.

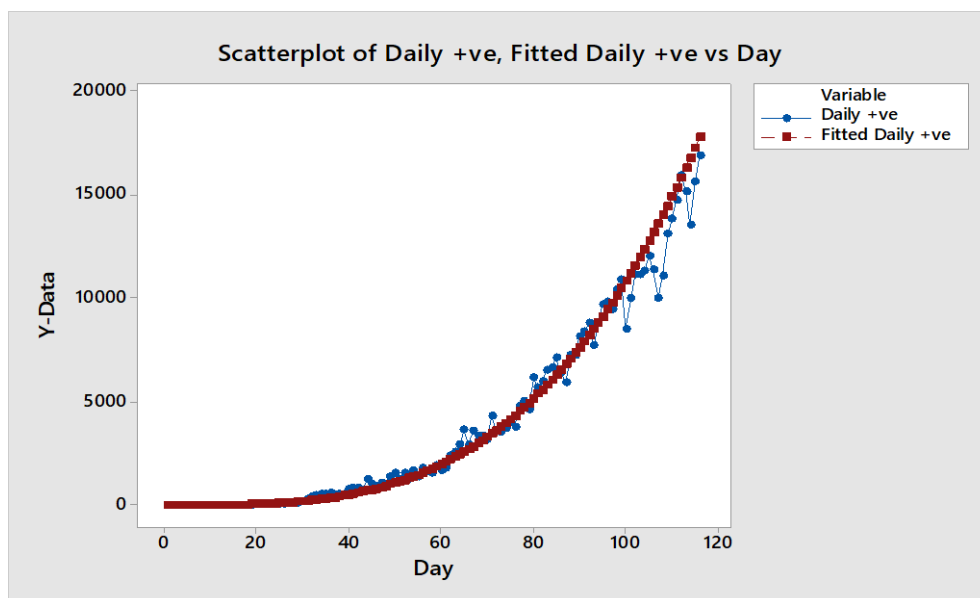


Figure 3: observed and fitted Daily +ve

Table 3: Predicted Daily and Cumulative +ve with Prediction limits for India

Date	Observed Daily +ve	Predicted Daily +ve	LPL of Of Daily +ve	UPL Daily +ve	Observed Cumulative +ve	Predicted Cumulative +ve	LPL of Cumulative +ve	UPL of Cumulative +ve
1 July	19429	21598	17774	25963	605221	612377	587156	641261
2 July	21947	22189	18289	26636	627168	634566	605445	667897
3 July	22718	22791	18815	27321	649886	657357	624260	695218
4 July	24018	23404	19350	28018	673904	680761	643610	723236
5 July	23942	24029	19897	28727	697846	704790	663507	751963
6 July	22500	24666	20454	29450	720346	729456	683961	781413
7 July	23145	25314	21022	30184	743491	754770	704983	811597
8 July	25561	25974	21601	30932	769052	780744	726584	842529
9 July	25790	26646	22191	31692	794842	807390	748775	874221
10 July	27762	27330	22792	32465	822604	834720	771567	906686
11 July	27757	28026	23404	33252	850361	862746	794971	939938
12 July	29106	28735	24028	34052	879467	891481	818999	973990
13 July	28178	29456	24663	34865	907645	920937	843662	1008855
14 July	29917	30189	25310	35691	937562	951126	868972	1044546
15 July	32607	30936	25969	36532	970169	982062	894941	1081078
16 July	35418	31695	26640	37386	1005587	1013757	921581	1118464
17 July	34824	32467	27323	38253	1040411	1046224	948904	1156717
18 July	37411	33252	28018	39135	1077822	1079476	976922	1195852
19 July	40235	34050	28725	40031	1118057	1113526	1005647	1235883
20 July	36806	34862	29444	40942	1154863	1148388	1035091	1276825
21 July	39170	35687	30176	41866	1194033	1184075	1065267	1318691
22 July	45601	36526	30921	42806	1239634	1220601	1096188	1361497
23 July	48443	37378	31679	43760	1288077	1257979	1127867	1405257
24 July		38244	32449	44728		1296223	1160316	1449985
25 July		39125	33232	45712		1335348	1193548	1495697
26 July		40019	34029	46711		1375367	1227577	1542408
27 July		40927	34838	47724		1416294	1262415	1590132
28 July		41850	35662	48754		1458144	1298077	1638886
29 July		42787	36498	49798		1500931	1334575	1688684
30 July		43739	37348	50858		1544670	1371923	1739542
31 July		44706	38212	51934		1589376	1410135	1791476
1 Aug		45687	39090	53026		1635063	1449225	1844502
2 Aug		46684	39982	54134		1681747	1489207	1898636
3 Aug		47695	40888	55258		1729442	1530095	1953894
4 Aug		48722	41809	56398		1778164	1571904	2010292
5 Aug		49764	42743	57554		1827928	1614647	2067846
6 Aug		50822	43693	58727		1878750	1658340	2126573
7 Aug		51895	44657	59917		1930645	1702997	2186490
8 Aug		52984	45635	61124		1983629	1748632	2247614
9 Aug		54089	46629	62347		2037718	1795261	2309961
10 Aug		55210	47637	63587		2092928	1842898	2373548
11 Aug		56347	48661	64845		2149275	1891559	2438393
12 Aug		57500	49700	66120		2206775	1941259	2504513
13 Aug		58670	50755	67412		2265445	1992014	2571925
14 Aug		59857	51825	68722		2325302	2043839	2640647

15 Aug		61060	52910	70050		2386362	2096749	2710697
16 Aug		62280	54012	71396		2448642	2150761	2782093
17 Aug		63517	55129	72759		2512159	2205890	2854852
18 Aug		64771	56263	74141		2576930	2262153	2928993
19 Aug		66042	57412	75541		2642972	2319565	3004534
20 Aug		67330	58578	76959		2710302	2378143	3081493
21 Aug		68637	59761	78396		2778939	2437904	3159889
22 Aug		69960	60960	79852		2848899	2498864	3239741
23 Aug		71302	62176	81326		2920201	2561040	3321067
24 Aug		72661	63408	82820		2992862	2624448	3403887
25 Aug		74039	64658	84333		3066901	2689106	3488220
26 Aug		75434	65925	85864		3142335	2755031	3574084
27 Aug		76848	67209	87416		3219183	2822240	3661500
28 Aug		78280	68510	88986		3297463	2890750	3750486
29 Aug		79731	69829	90577		3377194	2960579	3841063
30 Aug		81201	71166	92187		3458395	3031745	3933250
31 Aug		82690	72520	93817		3541085	3104265	4027067

LPL: Lower Prediction Limit ; UPL: Upper Prediction Limit

#### 4. Time Series Modelling of Daily +ve

Intuitively the number of positive cases detected on a particular day is very much likely to depend on the number of cases found on previous days. Therefore, we would like to model the Daily +ve data using time series modelling. In particular we shall be fitting ARIMA model to the data. In order to do this, we need to plot the auto-correlation function (ACF) and partial auto-correlation function (PACF) of the data on Daily +ve. The ACF and PACF of the Daily +ve data is shown in the figure 4 and figure 5 respectively. The tapering spikes of ACF as the lag increases suggests an AR model and the significance of PACF only at lag 1 indicates that an AR(1) model could appropriate. Before fitting of the model, we need to make sure that the data is stationary but we know that there is an exponentially increasing trend in the data. Hence, data is not stationary and we need to make the transformation.

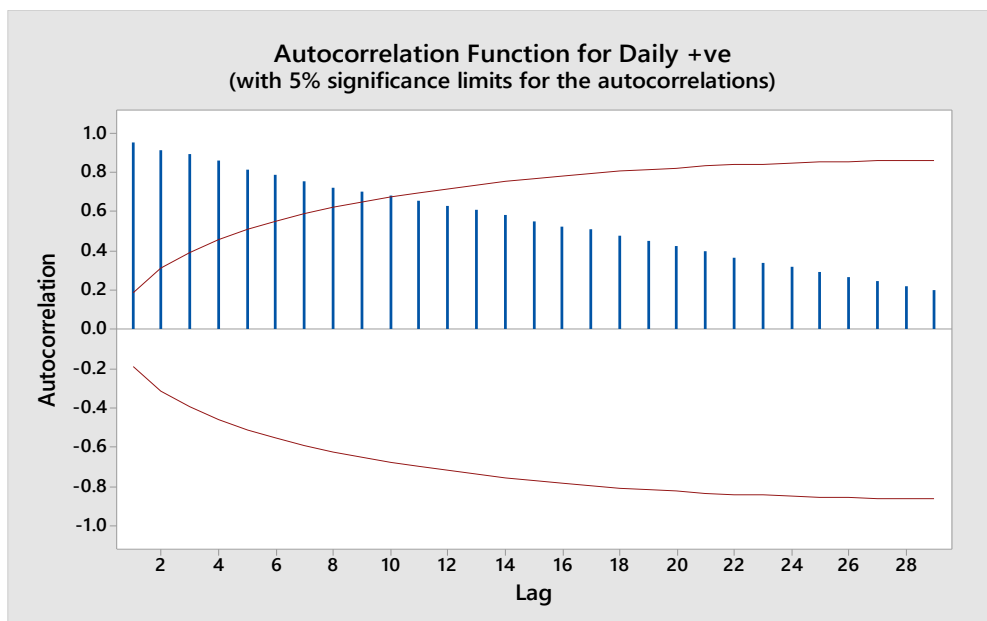


Figure 4: ACF of Daily +ve

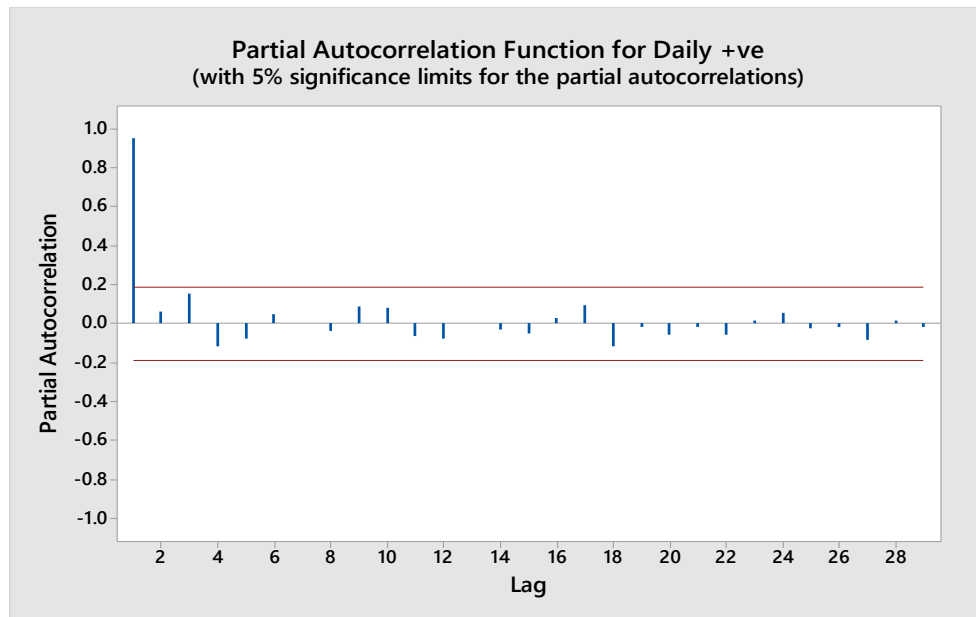


Figure 5: PACF of Daily +ve

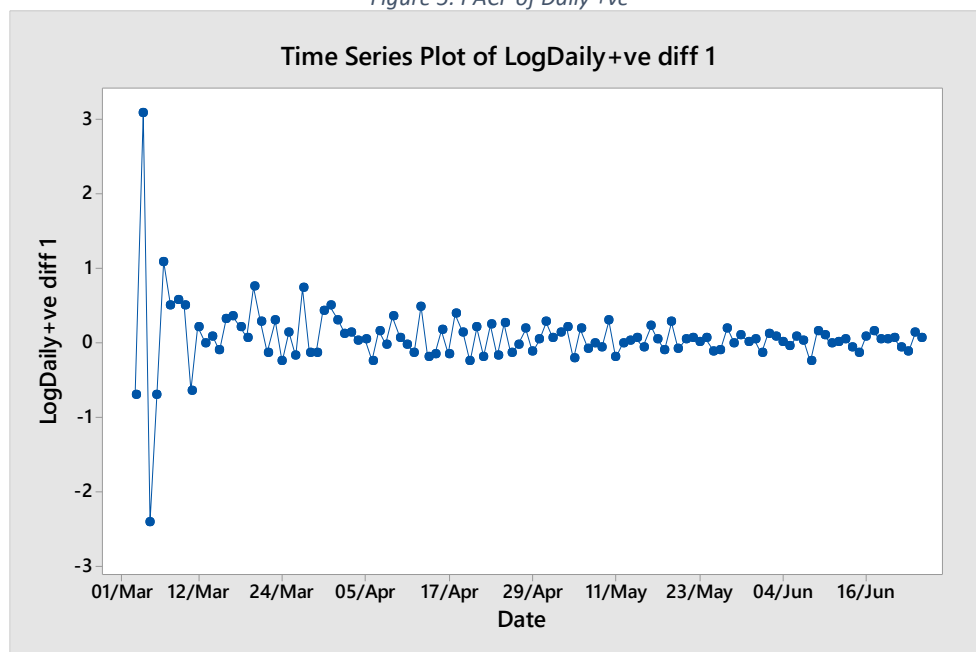


Figure 6: Time series plot of first order differenced log Daily +ve

We first filtered the data using first order differencing yet there was too much fluctuation in the variation and the stationarity could not be achieved. To reduce the variation, we tried the applying log on the original data and then finding the first order differencing. The time series plot of this filtered data is shown in the Figure 6. If we inspect the figure 6, we can observe that except for few points in the beginning the plot looks stationary. Therefore, we decided to drop the data for 2<sup>nd</sup> March through 11<sup>th</sup> March and plot the first order differenced log (Daily +ve) since 12<sup>th</sup> March onwards up to 24<sup>th</sup> June, the plot of which for 105 observations is given in Figure 7. It can be noticed that if it weren't for the few points like 20<sup>th</sup>, 27<sup>th</sup>, 30<sup>th</sup> and 31<sup>st</sup> March the plot in Figure 7 is approximately stationary. Similar is the case with second order differenced data of log(Daily +ve) for 12<sup>th</sup> March onwards. Its plot is produced as the figure 8.

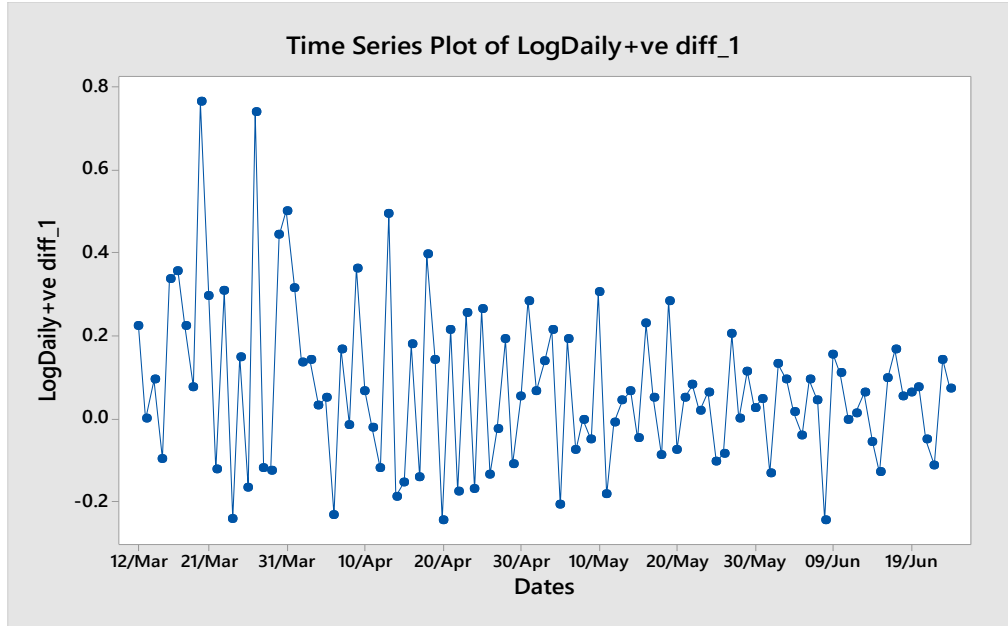


Figure 7: Time series plot of first order differenced log Daily +ve for the period 12<sup>th</sup> March – 24<sup>th</sup> June

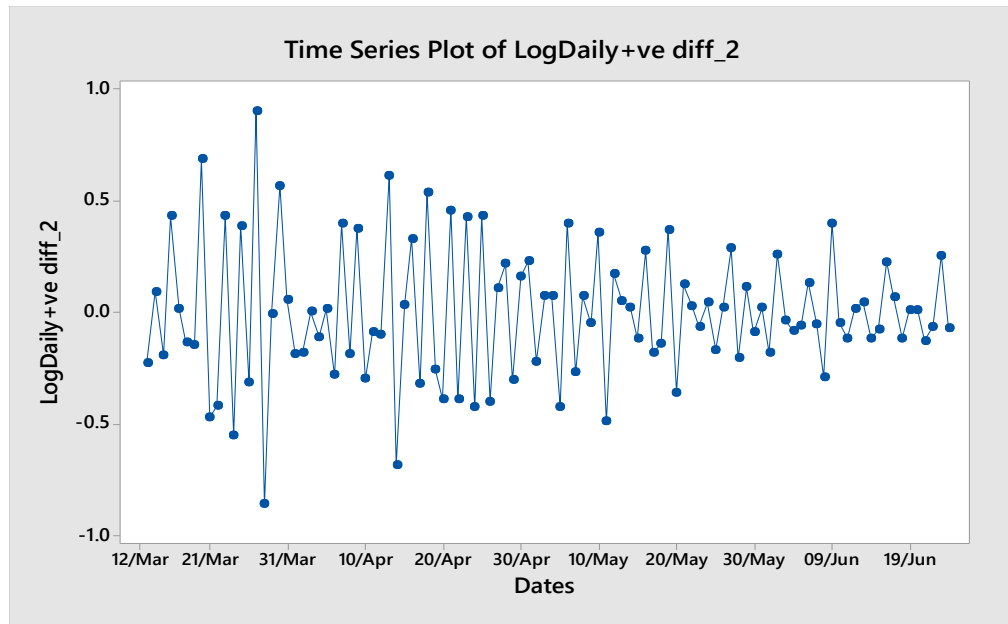


Figure 8: Time series plot of second order differenced log Daily +ve for the period 12<sup>th</sup> March – 24<sup>th</sup> June

Hence we fit several different models for  $\log(\text{Daily +ve})$ . The best fit model we found is ARIMA(2,1,1) with no constant. The final estimates of the parameters are given in the Table 4. The significance of the parameters is tested using t-test with p-value very small for all. This indicates that all the parameters are significant. The model fit is

$$y_t = 0.7730 y_{t-1} + 0.2247 y_{t-2} + e_t + 0.95 e_{t-1} \quad (2)$$

where  $y_t = x_t - x_{t-1}$  and  $x_t = \log(\text{Daily +ve})$  at time  $t$ . We can express the model in (2) in terms of  $x_t$  by simply substituting for  $y_t$ .

Table 4: Final estimate of the parameters

Type	Coef	SE Coef	T-Value	P-Value
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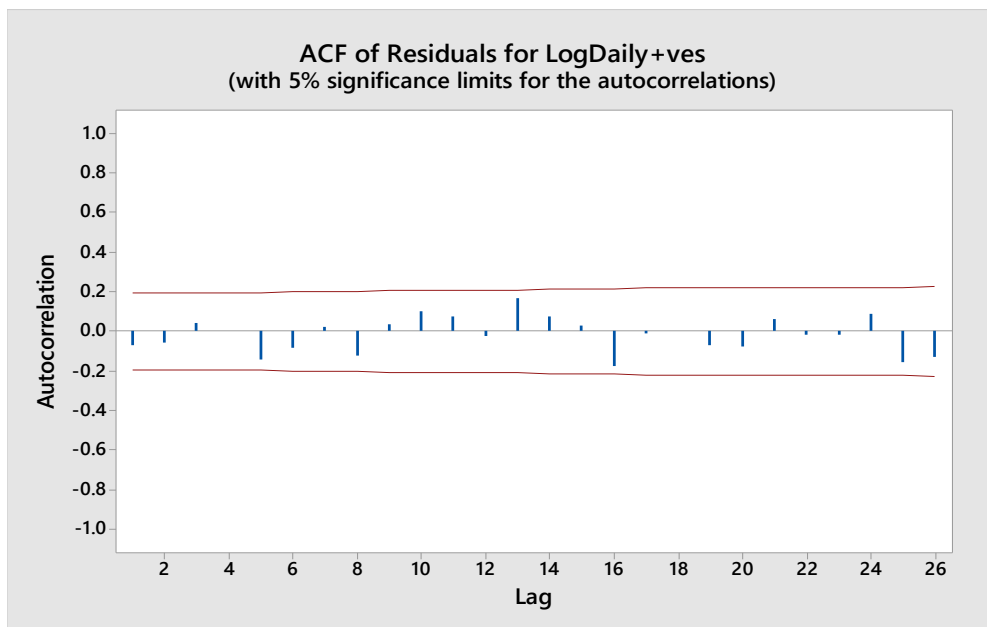
<b>AR 1</b>	0.7730	0.0994	7.77	0.000
<b>AR 2</b>	0.2247	0.0980	2.29	0.024
<b>MA 1</b>	0.9500	0.0330	28.83	0.000

The table 5 displays the Mean Sum of Square which is smallest for (2) as compared to the other models.

*Table 5: Residual sum of squares*

<b>DF</b>	<b>SS</b>	<b>MS</b>
101	3.57837	0.0354295

The residuals must not be auto correlated and this is apparent in Figure 9 with autocorrelation being insignificant at all the lags.



*Figure 9: ACF of residuals for ARIMA(2,1,1)*

The significance of the autocorrelation among residuals at four lags is tested using Ljung-Box Chi-Square Statistics and output is shown in the Table 6. The p-values for the test at all the four lags are very large pointing towards the insignificance of autocorrelation among residuals.

*Table 6: Modified Box-Pierce (Ljung-Box) Chi-Square Statistic*

<b>Lag</b>	12	24	36	48
<b>Chi-Square</b>	8.02	19.14	30.78	37.65
<b>DF</b>	9	21	33	45
<b>P-Value</b>	0.533	0.576	0.578	0.773

Also, the residuals are normally distributed which can be observed in the NPP and histogram in top-left and bottom-left corner of the Figure 10. The error has constant variance which is evident from the graph of residual against the fitted values in the top-right corner of the figure 10. One may have the

impression that the variance is not constant for the error but it can be noticed that it is happening due to the just three residual values at the top of the graph out of 101 residuals which can be ignored.

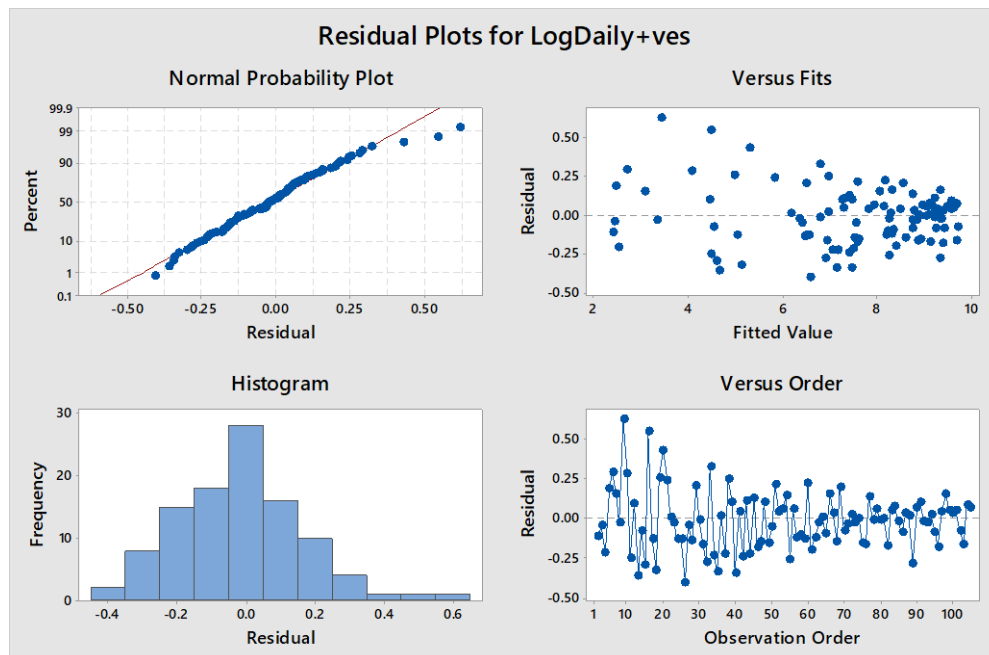


Figure 10: residual plot for ARIMA(2,1,1)

Now that we have fit the best possible model with all the assumptions being satisfied, we move to our main purpose of forecasting. But before that we would like to see how well the model fits in the data graphically. This can be seen in the figure 11 which is time series plot of the observed and fitted Daily +ve.

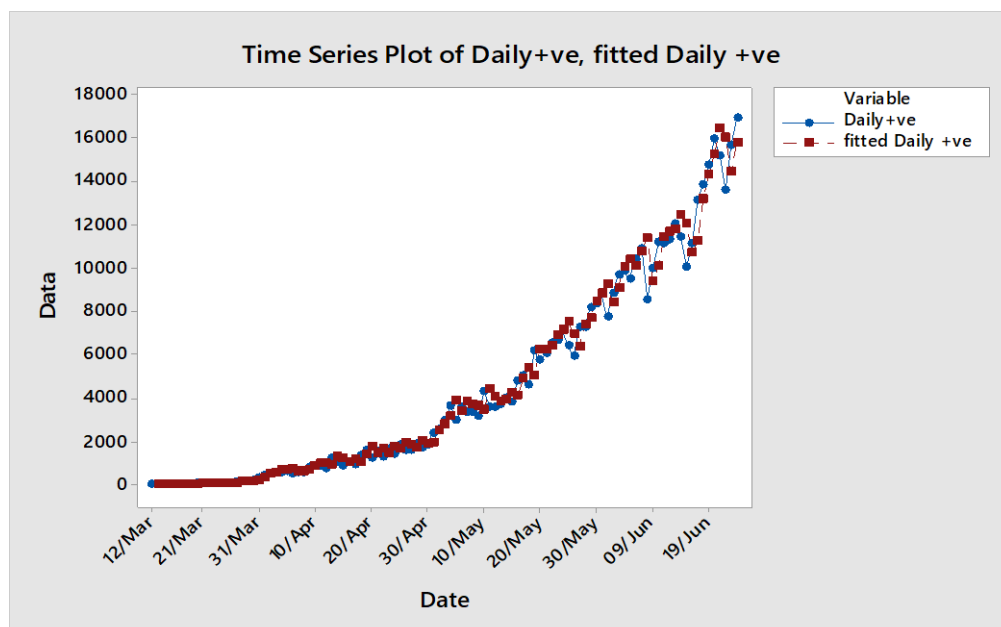


Figure 11: Time series plot of observed Daily +ve and fitted Daily +ve through ARIMA(2,1,1)

The forecast for lead time = 10, i.e. for 10 days ahead of 24<sup>th</sup> June for log(Daily +ve) is given in the table 7 with 95% confidence limits.. We must undo the transformation to get the forecasts for Daily +ve. For this we need to raise the given forecasts and the confidence limits to the power of e.

Table 7: Forecast for 10 Days from 25<sup>th</sup> June for Log(Daily +ve) using ARIMA(2,1,1)

			95% Limits	
Period	Date	Forecast	Lower	Upper
106	25 June	9.7593	9.39033	10.1283
107	26 June	9.7963	9.31839	10.2742
108	27 June	9.8308	9.24647	10.4151
109	28 June	9.8657	9.18636	10.5451
110	29 June	9.9005	9.13073	10.6702
111	30 June	9.9352	9.07848	10.7919
112	1 July	9.9699	9.02831	10.9114
113	2 July	10.0045	8.97954	11.0294
114	3 July	10.0390	8.93165	11.1463
115	4 July	10.0734	8.88428	11.2626

The back-transformed forecasts are given in the Table 8 rounded to the nearest integers.

Table 8: Forecasts for 10 Days from 25<sup>th</sup> June for Daily +ve using ARIMA(2,1,1)

			95% Limits	
Period	Date	Forecast	Lower	Upper
106	25 June	17315	11972	25042
107	26 June	17967	11141	28975
108	27 June	18598	10368	33360
109	28 June	19258	9763	37991
110	29 June	19940	9235	43054
111	30 June	20644	8765	48625
112	1 July	21373	8336	54798
113	2 July	22126	7939	61661
114	3 July	22902	7568	69307
115	4 July	23704	7218	77855

## 5. Analysis of Active Cases

Define  $X_t$  = Total Active Cases on day t

Define  $C_t = X_{t+1}/X_t$

This is the ratio of total active cases today and same on yesterday. As long as the total active cases keep increasing the ratio  $C_t$  will be greater than unity. But when the total active cases today are greater than yesterday then this ratio falls below unity and remain consistently below but close to unity if the

situation keeps getting better every day. Therefore,  $C_t$  can be used to predict the day on and after which the active cases start rolling down. This will happen on the day  $C_t$  falls below unity.

The ratio  $C_t$  cannot be used to predict the end of the pandemic. This ratio will become zero only if for a given  $t$ ,  $X_{t+1}$  is zero but this does not indicate the eradication of the pandemic because the on  $t+2$  active cases may appear again. Besides technically  $C_t$  can be equal to unity if on two or more consecutive days the number of new active cases are same even though these cases are large in number.

To understand how this ratio  $C_t$  has been varying in India, see the figure 12 which plots  $C_t$  against  $t$  from 4<sup>th</sup> April through 16<sup>th</sup> July.

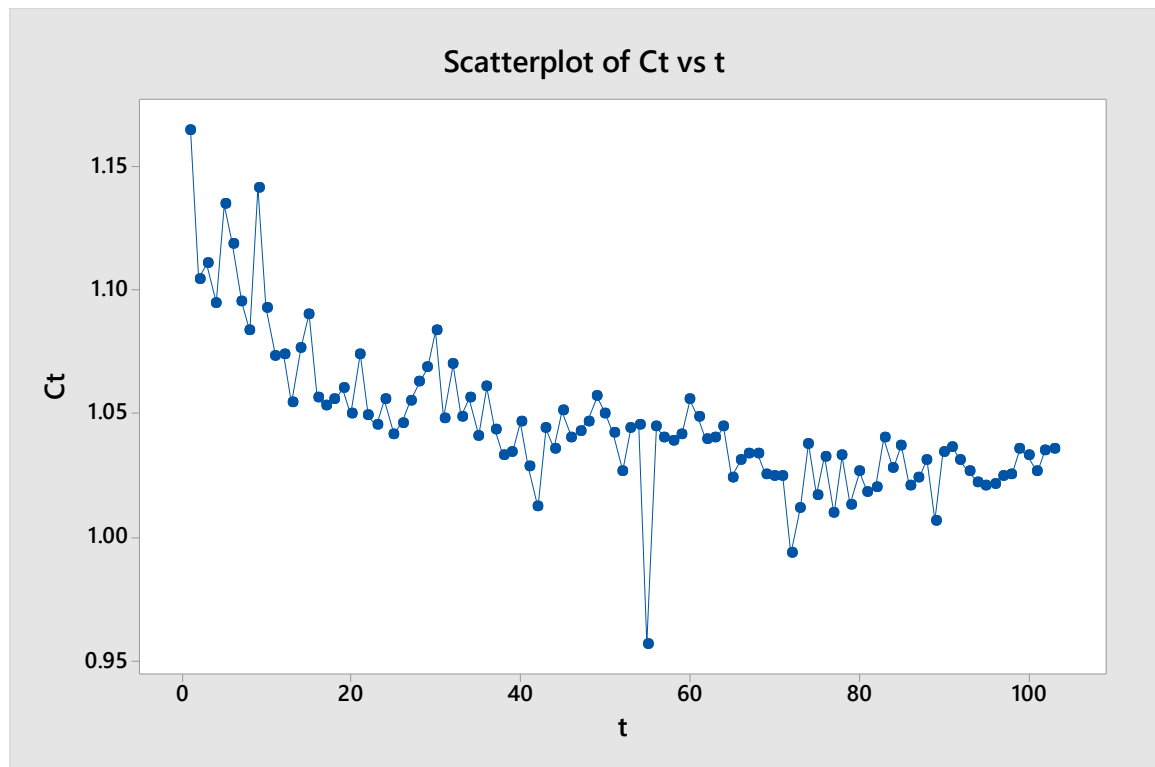


Figure 12

We can observe that this ratio  $C_t$  has been decreasing exponentially. To linearize the relationship, we plotted the graph of  $\log C_t$  against  $t$  and fitted the model but it wasn't satisfactory. We also plotted the  $\log C_t$  and  $\log t$ . The plot is given below in figure 13 and we can observe the linear relationship between  $\log C_t$  and  $\log t$  with negative slope.

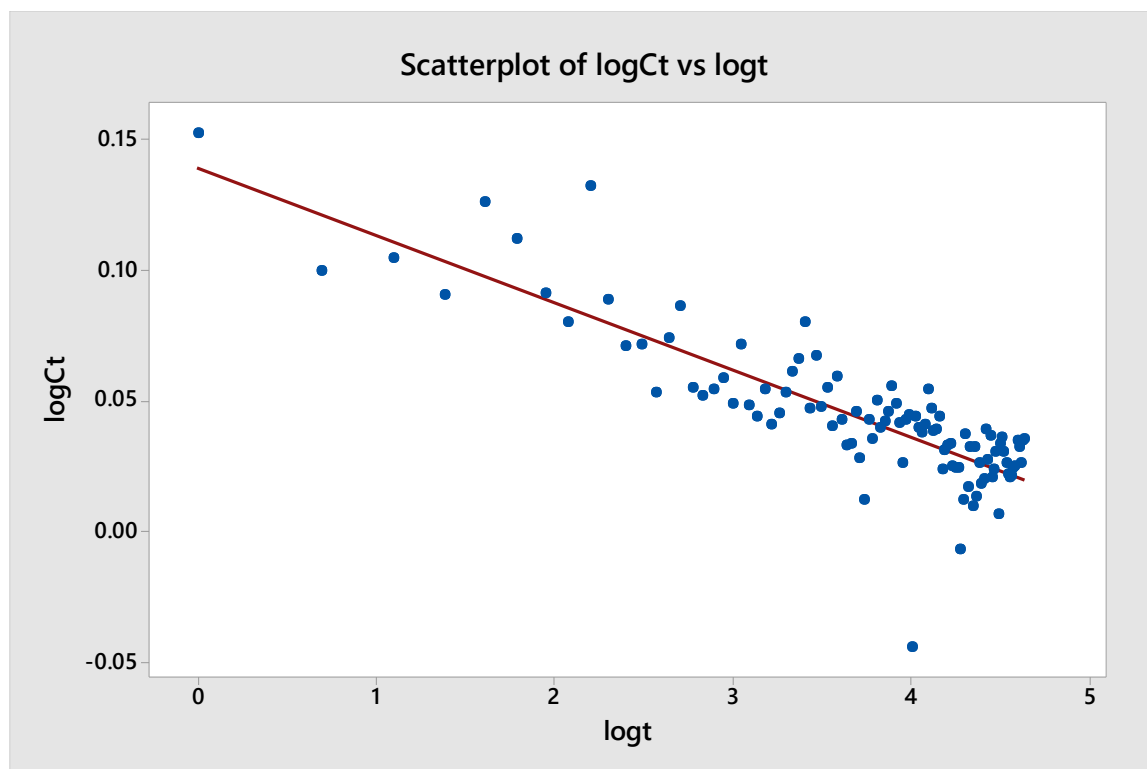


Figure 13

We fit the linear regression for  $\log C_t$  against  $\log t$

## Regression Analysis: $\log C_t$ versus $\log t$

### Regression Equation

$$\log C_t = 0.13961 - 0.02578 \log t \quad (3)$$

### Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	1	0.05857	0.058565	261.82	0.000
logt	1	0.05857	0.058565	261.82	0.000
Error	101	0.02259	0.000224		
Total	102	0.08116			

### Model Summary

R-sq	R-sq(pred)
72.16%	70.89%

### Coefficients

Term	Coef	SE Coef	T-Value	P-Value
Constant	0.13961	0.00602	23.17	0.000
logt	-0.02578	0.00159	-16.18	0.000

## Durbin-Watson Statistic

Durbin-Watson Statistic = 1.82298

We can observe Durbin-Watson statistic is close to 2 indicating no autocorrelation among the residuals. Also, the residual plot shown in figure 14 justifies the validity of assumptions.

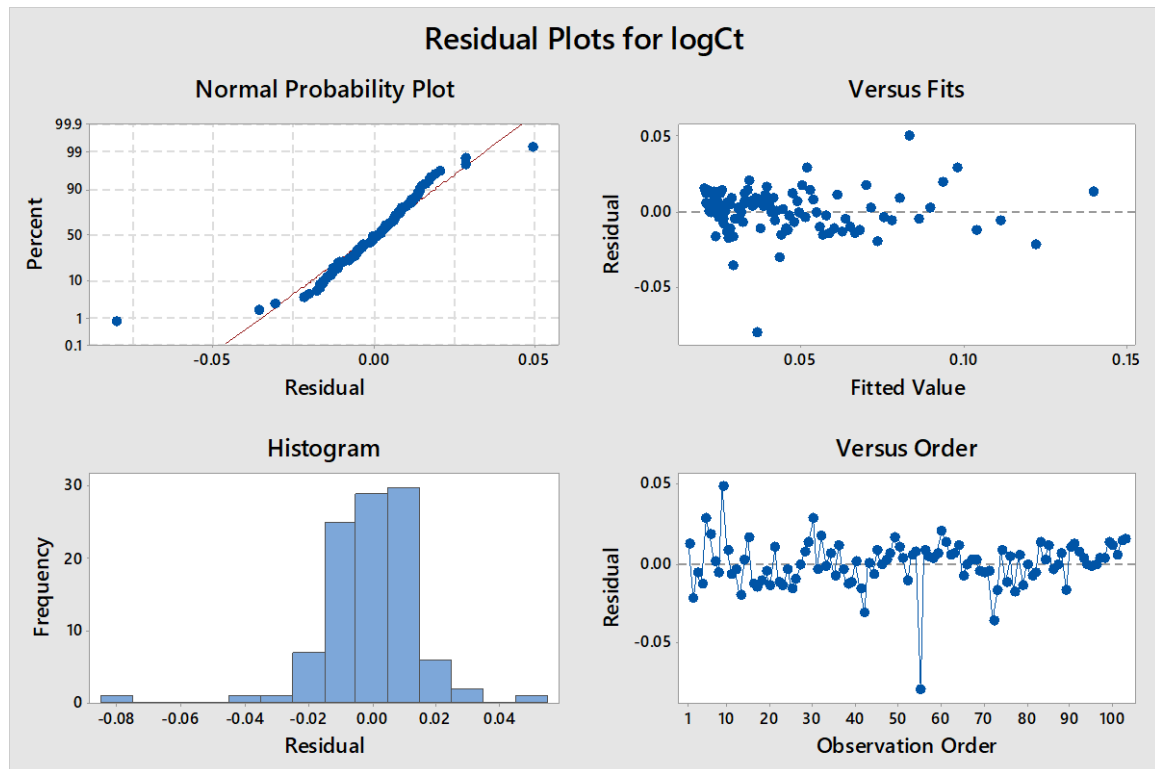


Figure 14

The figure 15 plots the  $R_t$  and fitted  $R_t$  found using the regression model  $\log R_t = 0.13961 - 0.02578 \log t$

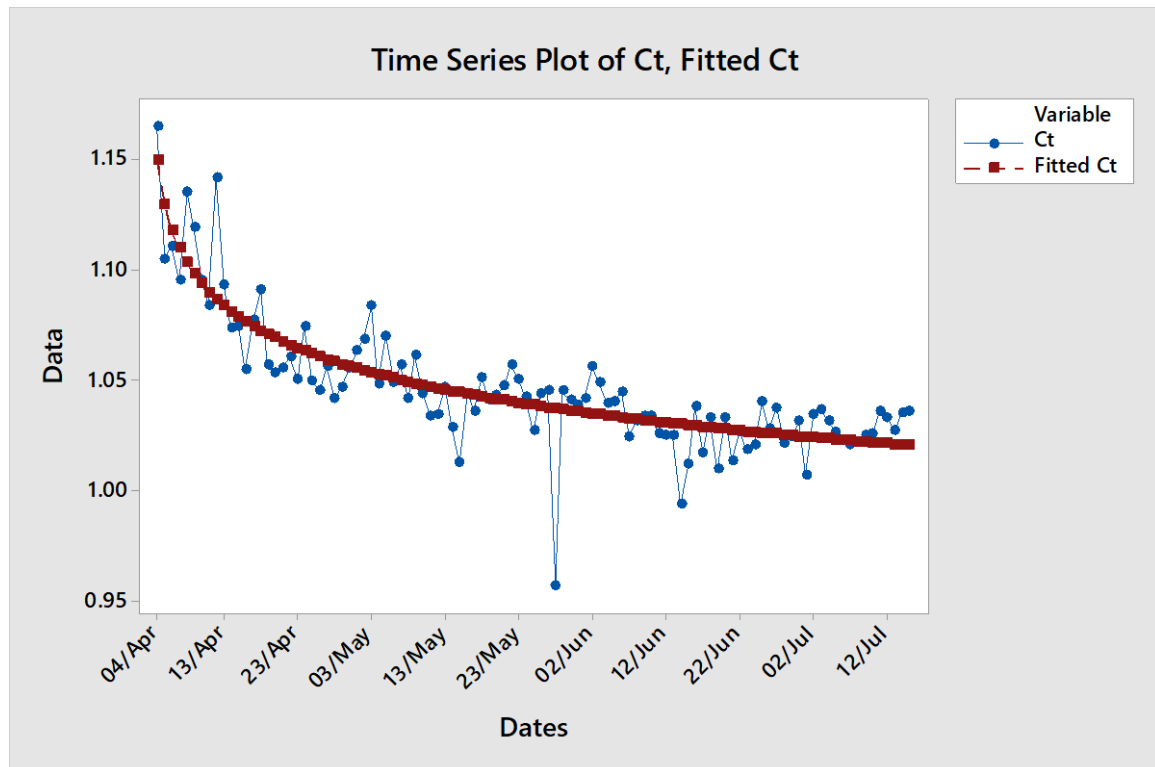


Figure 15

Now we want to determine the day on which ratio  $R_t$  becomes 1. That is, the day Total Active Cases ( $X_t$ ) starts rolling down. For this we solve the regression equation for  $t$  when  $R_t = 1$  and we find that for  $t = 229$ ,  $R_t = 1$ . In our data  $t = 1$  for 4<sup>th</sup> April. Hence, as per the model it can be expected that from about 18<sup>th</sup> Nov 2020 the new Active Cases found daily starts decreasing in India.

## 6. Analysis of Recovery Rate

Following is the graph of 'Recovery Rate' in India in figure 16.

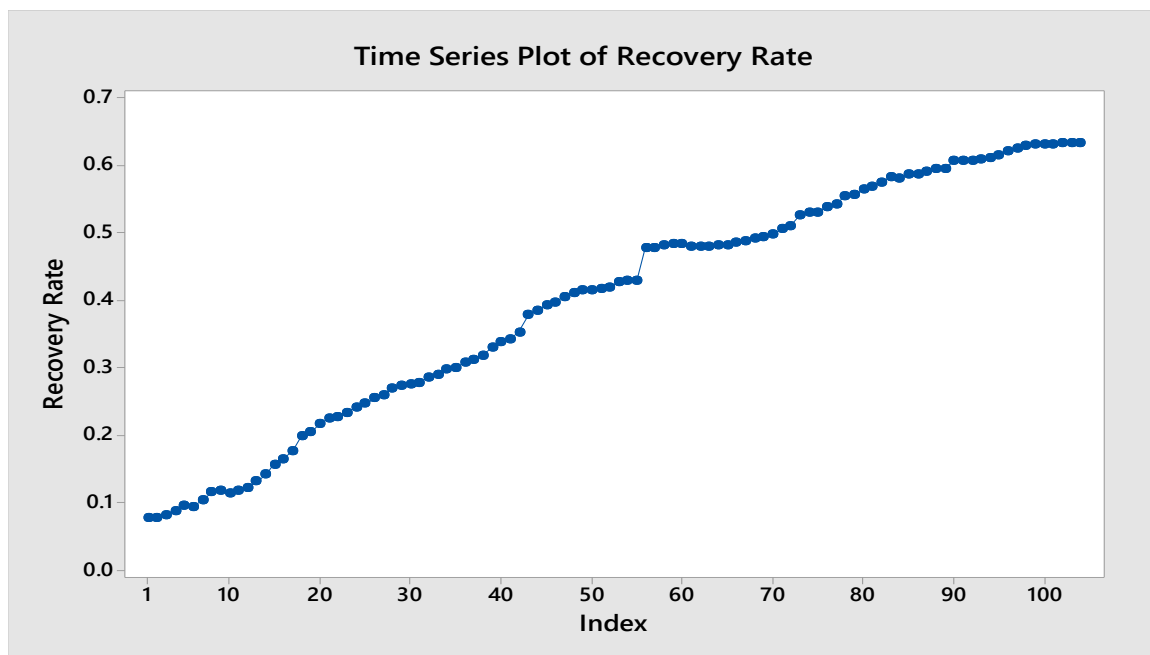


Figure 16

We define recovery rate =  $R_t = D_t / Y_t$

Where  $D_t$  = Total discharged/recovered patient until day  $t$

$Y_t$  = total covid-19 positive cases until day  $t$

We can observe that recovery rate has been consistently increasing. This means the rate of increment of recovering patients is greater than the rate of increment in total positive. The day recovery rate unity indicates on the day total number of recovered patients are equal to total number of positive cases. That is, all the positive cases found so far have been recovered and implies the end of the pandemic. Also, once this recovery rate hits unity any newly found cases will also be cured with the same rate and surge in the cases will be curbed.

$R_t$ 's are undoubtedly autocorrelated and figure 17 shows the autocorrelation function of the  $R_t$  for various lags. The tapering spikes indicates the model could be Autoregressive model.

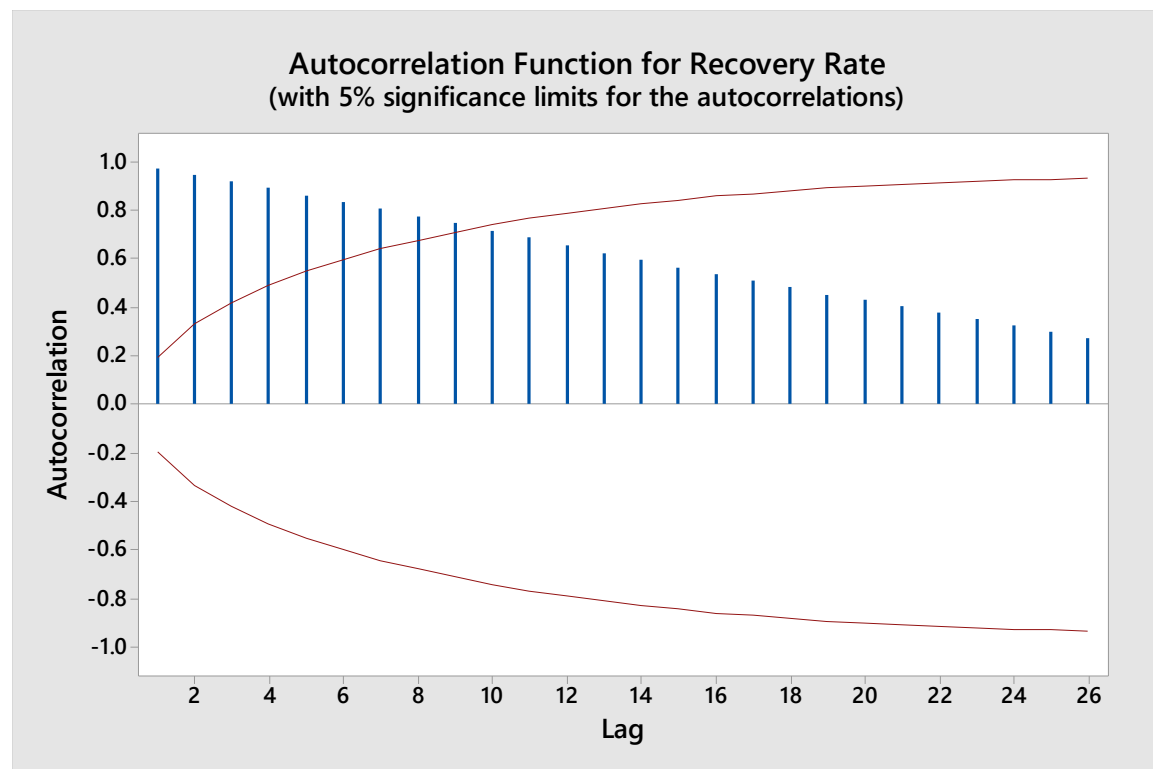
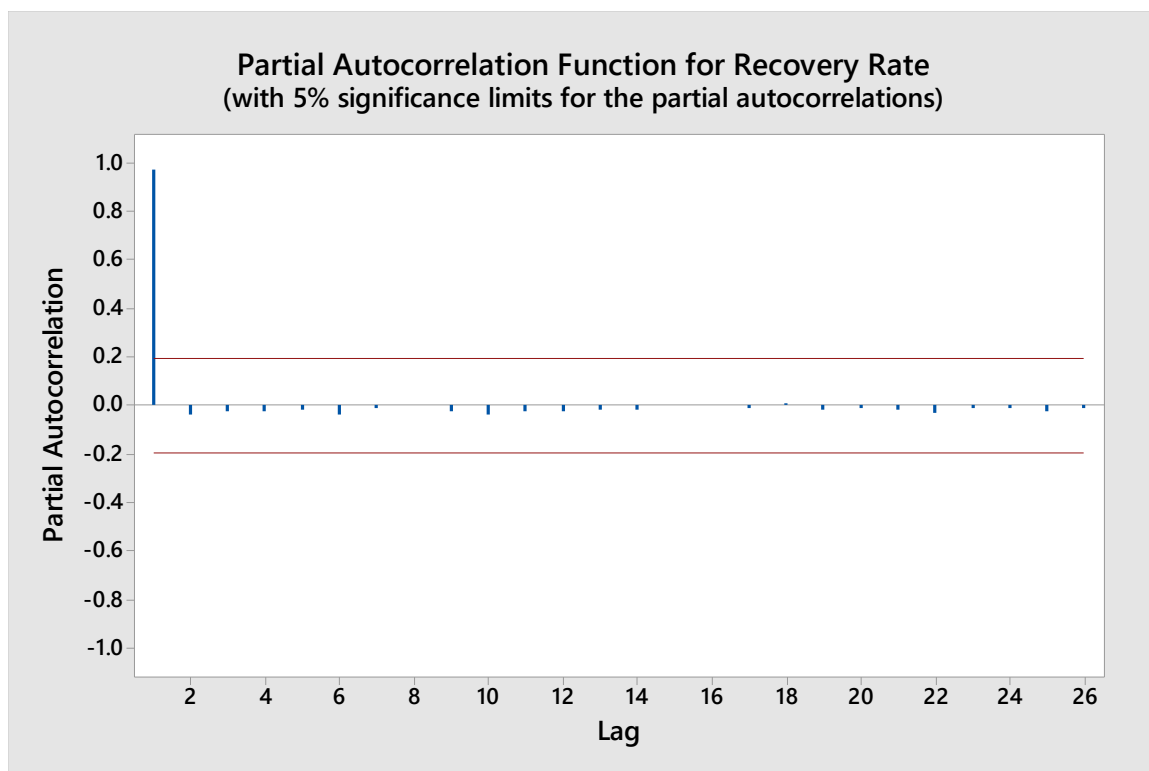


Figure 17

In the figure 18 we see that partial autocorrelation is significant only at lag 1. This indicates that the tentative model could be AR(1).





*Figure 18*

We model  $R_t$  against  $R_{t-1}$  using least square method.

## Regression Analysis: Recovery Rate versus Recovery Rate lag1 Method

Box-Cox transformation

Rounded  $\lambda$                       1  
 Estimated  $\lambda$                     1.02717  
 95% CI for  $\lambda$                   (0.997674, 1.05767)

### Regression Equation

$$R_t = 0.00867 + 0.99170 R_{t-1} \quad (4)$$

### Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	1	3.04794	3.04794	79146.34	0.000
$R_{t-1}$	1	3.04794	3.04794	79146.34	0.000
Error	101	0.00389	0.00004		
Total	102	3.05183			

## Model Summary

R-sq	R-sq(pred)
99.87%	99.87%

## Coefficients

Term	Coef	SE Coef	T-Value	P-Value
Constant	0.00867	0.00152	5.70	0.000
$R_{t-1}$	0.99170	0.00353	281.33	0.000

## Durbin-Watson Statistic

Durbin-Watson Statistic = 1.95283

Durbin-Watson statistic is very close to 2 indicating here is not autocorrelation among residuals. Also, the residuals are satisfactorily justifying the assumption made for regression model.

## Residual Plots for Recovery Rate

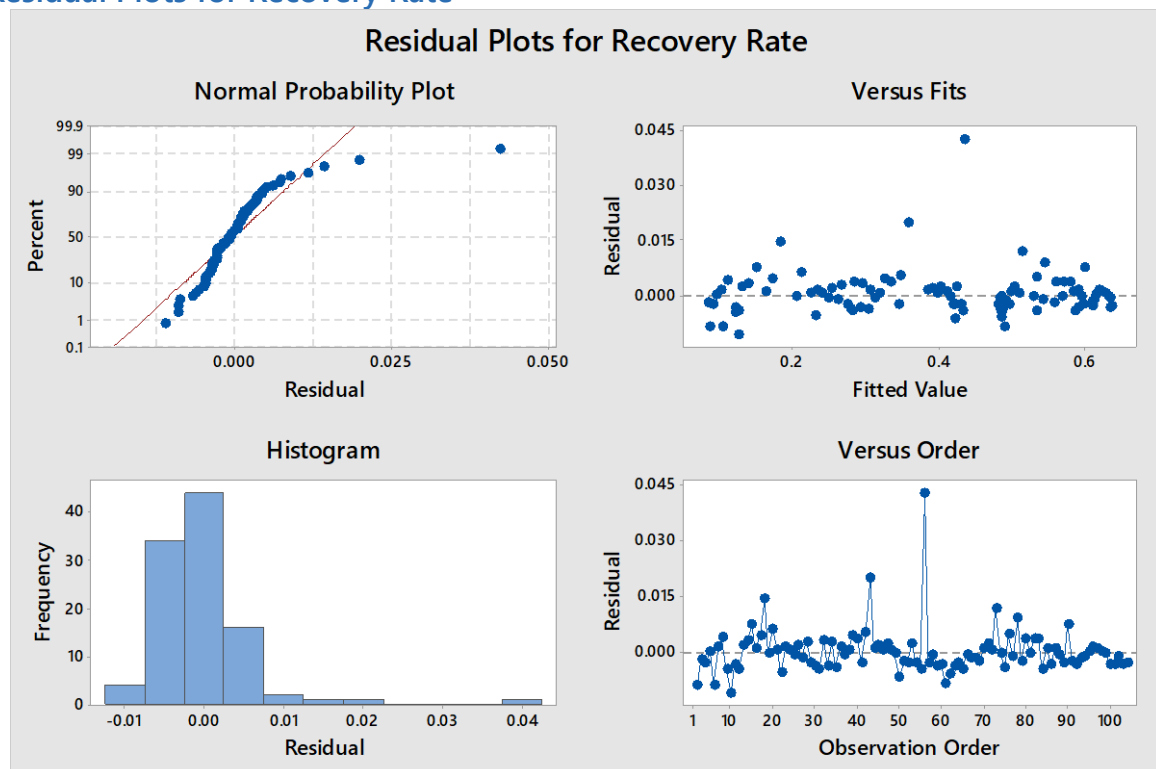


Figure 19

The figure 20 demonstrates the observed and fitted recovery rate. Now we will be determining the 't' for which  $R_t$  hits unity. So, if the situation remains the same then as per above model, the recovery rate will become one on 368<sup>th</sup> day where 4<sup>th</sup> April 2020 is the day one. This means by 9<sup>th</sup> April 2021 the recovery rate reaches 100%. This indicates all the covid-19 patients will be recovered by about 9<sup>th</sup> April 2021 and hence the pandemic will end in India.

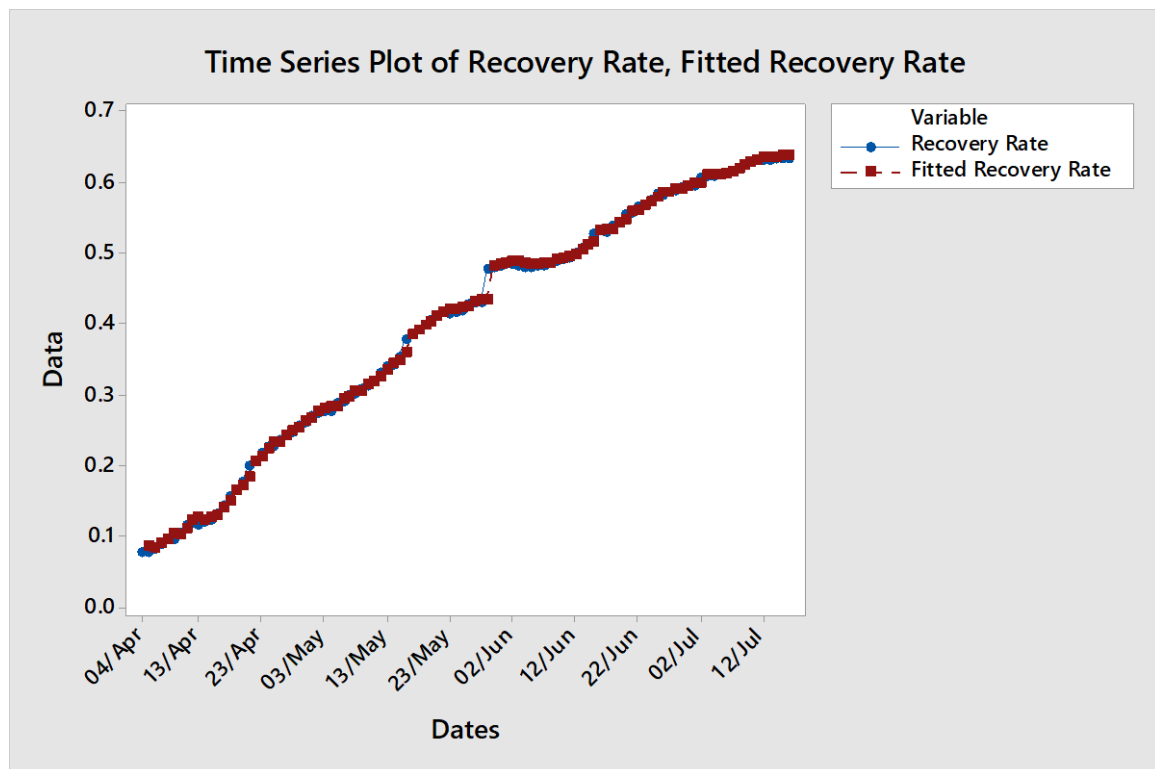


Figure 20

It must be mentioned that in case of invention of effective vaccines the recovery rate could improve even more and the pandemic can end even earlier. Figure 21 shows the observed and predicted recovery rate.

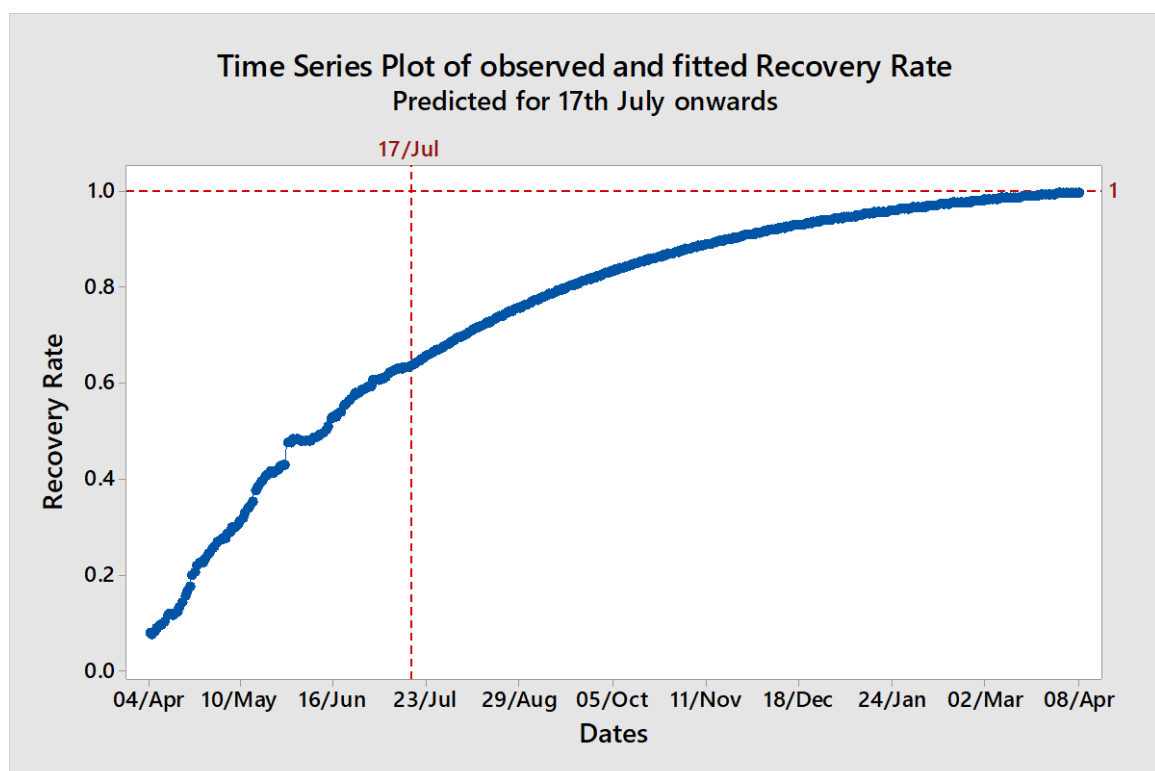


Figure 21

Following table lists some predicted recovery rate in percentage for various dates.

Table 9

Date	Recovery rate %	Date	Recovery rate%
16/07/2020	63.3	31/10/2020	87.6
21/07/2020	65.0	19/11/2020	90.1
31/07/2020	68.1	30/11/2020	91.3
07/08/2020	70.2	31/12/2020	94.3
25/08/2020	75.0	08/01/2021	95.0
31/08/2020	76.4	31/01/2021	96.6
17/09/2020	80.1	28/02/2021	98.3
30/09/2020	82.6	31/03/2021	99.7
14/10/2020	85.0	08/04/2021	100

The following R-command is used to predict the recovery rate ( $R_t$ ) iteratively.

```
R=NULL
```

```
R[1]=0.633031
```

```
for(i in 2:270){
```

```
  RR[i]=0.00867+0.9917*RR[i-1]
```

```
}
```

```
R
```

## 7. Conclusion

- 1) In India, the model predicted that the cumulative number of positive cases may hit the figure of 10,00,000 by 16<sup>th</sup> of July and it happened exactly on the same day with 10,05,637 cases. (refer Table 3).
- 2) By the end of July, the cumulative +ve cases may rise to 15 lacs as per the model. The 20 lac cumulative cases may be hit by the end of first week of August. By the end of Aug the total cases may rise beyond 35 lacs.
- 3) The situation remains the same overall for the whole country and the Daily +ve cases rise at the same rate they have been rising so far then from third week of July every fourth day 1 lac new cases will be added to the number of cumulative +ve cases. (refer Table 3).
- 4) As per the model the Daily +ve cases can hit the mark of 50,000 by 6<sup>th</sup> Aug. It may happen by 30<sup>th</sup> July at the earliest as per the model.
- 5) As per the model (3) it can be expected that from 18<sup>th</sup> Nov 2020 the new Active Cases added daily starts decreasing in India.
- 6) **As per model (4) all the covid-19 patients will be recovered by second week of April 2021 and hence the pandemic will end in India provided the conditions remain roughly the same.**

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